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Macroeconomic Forecasting: A Study of Profits

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Macroeconomic Forecasting: A Study of Profits

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Dedication

Jahshanti Allen:

Hollis, Queens, NY This is for you.

Kristy Giacoman:

To my parents, Karime Favela and Omar Giacoman for their dedicated partnership for success in my life;

To my sister, Karol Giacoman for being a source of inspiration and motivation to my drive;

To the proud citizens of my country located in the United States, that came looking for better opportunities;

This research is dedicated to you.

Acknowledgments

We would like to thank Professor Michael Radzicki of the Worcester Polytechnic Institute Department of Economics for serving as an advisor and mentor to the development of this project.

We would also like to thank the FED for facilitating data on the U.S. Economy to all general public through their website, thank you for helping us do research.

Without the support and expertise of these people, the success of the project would not have been possible.

Abstract

With a basis on the analytical framework of Levy and Kalecki's Corporate Profits Equations, this research uses Machine Learning and Deep Learning approaches to provide a reliable forecast for aggregate corporate profits in the United States economy. The principal tool used to deliver this forecasting method was the RapidMiner Software and the data source for the variables in the equation was the Federal Reserve Bank of St. Louis. Making use of these predictions and relying on economic theory, this paper explores the repercussions of assumptions made since the early beginnings of Marxism, through the Cambridge Controversies, until today, regarding the relationships between the working class and the elite.

Chapter 1: Introduction

The goal of every business is to make profits, and desirably, to increase those profits year to year. In order to run a successful business, it seems almost evident that the owner or owners may find rather useful to know the profits that the company expects to make in the months to come. If one was to make predictions regarding the profits of their own business, one would have to define assumptions, study the market, project costs, and ultimately hope for the best, by keeping a considerable margin to maintain the forecast rather conservative. These predictions are commonly done in every industry, through revenue and expense forecasting, conducted by the CFOs of the bigger companies and by the accountants of the smaller ones.

Venturing through the task of figuring out what to explore for this project, we fumbled through several avenues. Being certain of wanting to use machine-learning technology to make predictions of variables that impact the economy, on initial thought, we naturally were pushed towards GDP. After studying the GDP NOW model and the Fair GDP Model, Gross Domestic Product forecasting seemed interesting, and predicting its value monthly and/or quarterly was the initial plan. However, since it had already been done before and had widely accepted methods for its prediction, we thought it would be better to stray away from the "norm".

Despite the monthly efforts of businesses to predict their earnings, and the widely known efforts of scholars to develop complex multi-sector models to predict GDP or GNP, little effort has been made to make predictions of profits in the aggregate economy. Perhaps the first attempt dates back a few decades, when Sidney R. Finkel and Donald L. Tuttle used a multiple linear regression technique to develop and test a model to explain and predict the profit margin at the macro level.[1] They chose to use their own set of variables to make the predictions including utilization of capacity, unit labor costs, a GNP deflator and a trade surplus.[2] For the purpose of this research, the variables used are those advised by Jerome Levy and Michal Kalecki in their profit equation, discussed later on this paper.

Now, why is it even remotely relevant to predict corporate profits on the aggregate? On initial thought, one may be able to draw relationships between economic collapses, debt, and employment in the United States and aggregate profits. Likewise, profits can also point us in the direction of the worker-capitalist relationship in this nation. "The importance of making accurate forecasts of aggregate corporate profits should be obvious. Future aggregate corporate profits are, of course, critically important to financial analysts who must make market judgements. They are also significant as a measure of growth of the economy since, in combination with the retention rate, they determine aggregate business savings and hence the potential capital formation ability of the economy."[3]

Most economic modeling and learning is formed on the basis of economic theory. To diverge from this method, the research done for this paper relies on data prediction based on Machine Learning. Firms want predictions so that they can anticipate when to slow down production, employment, and when to do the opposite. This project produces aggregate profit predictions in the United States economy and shows how it affects Macroeconomic issues in the country, its citizens, firms, etc.

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[1] Finkel, S., & Tuttle, D. (1971). Determinants of the Aggregate Profits Margin. The Journal of Finance, 26(5), 1067-1075. doi:10.2307/2326083

[2] Ibid

[3] Ibid

There is and always will be a duel between workers and capitalists in this nation and by using the profit equation by Kalecki and Levy, and our findings from great economic debates such as “The Cambridge Controversies”, we can make sense of the capitalist-worker relationship and predict what it will look like in the future. Data Science and Artificial Intelligence give us predictions without the need for a theoretical backbone, with pure “raw” science and math. This research provides those predictions, and only then analyzes their social impact based on some economic theory of the past.

Chapter 2: Background

2.1 Profit Equation

Profits are usually defined as the gain of selling minus the cost of buying, producing or operating something. However, when we talk about the aggregate profits, we define them through the Levy-Kalecki equation. The implications of this equation can provide guidance in identifying risks to the macroeconomy and capital markets. The variables for the Levy-Kalecki equation are Net Investment, Household Saving, Rest of the World (ROW) Saving, Government Saving, Dividends, and Statistical Discrepancy. In order to explain the Levy-Kalecki equation, one must understand that hoarding means to accumulate already existing wealth and investing means to create new wealth that didn't previously exist. This paper used a prior study done in 2013 that broke down the equation as you will see below.[4]

Investment = Saving of the whole economy

Now, the economy is commonly divided into sectors: Households, Corporations, Government, and the Rest of the World (ROW). This makes the equation be:

Investment = Household Saving + Corporate Saving + Government Saving + ROW Saving

At the same time, Corporate Saving can be furtherly explained

Corporate Saving = Corporate Profit - Dividends

By substituting and rearranging the equations, we get the Levy-Kalecki equation for aggregate profits:

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[4] "The Corporate Profit Equation Derived, Explained, Tested: 1929-2013." *PHILOSOPHICAL ECONOMICS*, 24 Nov. 2013, www.philosophicaleconomics.com/2013/11/cp/.

Aggregate Profits = Net Investment - Household Saving - Foreign Saving - Government Saving + Dividends

This equation tells us where profits originate, and it is true by definition, however, there are several papers such as "The Corporate Profit Equation Derived, Explained, Tested: 1929-2013" that provide an empirical confirmation.[5] This equation also states that if dividends are held constant, then any increase in saving that in the non-corporate sectors that is not offset by an increase in investment will require the corporate sector to save less. An increase in the private sector's wealth equals and increase in the public sector's debt. Lastly, economic growth and financial assets are linked to a growth in private sector borrowing and private sector debt. Profits can indicate the financial well-being on nation and can even indicate social impacts on its citizens.

2.2 Theories Surrounding Profit

Kalecki, of Eastern European descent, worked to understand profits and tie the concept into Marxist economic theory. The understanding profits brings us to the battle between Marxists and capitalists. From there we move closer to the present with the Cambridge Controversies up until modern day American politics.

2.2.1 Marxists and Capitalists

Karl Marx is the father of Marxist Communism. His goal was to fix capitalism. "He saw capitalism as an outmoded economic system that exploited workers, which would eventually rise against the rich because the poor were so unfairly treated.[6]" The fundamental communist

[5] Ibid

[6] "Comparing Economic Systems." *Ushistory.org*, Independence Hall Association, www.ushistory.org/gov/13b.asp.

principle was to stop private ownership. Private ownership encouraged greed and motivated people to knock out the competition, Marx believed. By ending greed and having the government provide stability Marx hoped to see disparity lessen.[7]

Capitalism, on the other hand, promotes the private sector and economic freedom.[8] capitalists, or owners, make decisions about products, pricing, and wages. Marxists believe these to be ingredients for exploitation and greed to grow. However, Capitalism is supposed to be put in balance by "The Invisible Hand" of Adam Smith. This ideology suggests that "Supply and Demand" always find the best price in a market.[9] The ideology also supports that firms that cannot compete naturally disappear and new firms are naturally born, as we see with competition and species within the Universe. The Invisible Hand can then be compared to a process of natural selection but for the market. To a Marxist, a firm making profit is awful, since they assume the capitalists are exploiting the workers and promoting greed. To a capitalist, profit is a sign of success in a competitive market place where being an owner is the ultimate risk.

We see the topic of exploitation continue throughout the 19th Century with Marxism into the 20th Century with the Cambridge Controversies. The Cambridge Controversies was not a Marxist vs Capitalism debate initially. It was a debate between Cambridge, United States versus Cambridge, England. More specifically, it was a debate between MIT and Cambridge University, and this debate was about Capital. "The essence of the debate revolved around the fundamental premises of the theories of value, distribution, and growth, each of which depends upon an aggregate production function where the inputs or factors of production for capital and labor are aggregated in some fashion prior to the determination of the rate of profit (interest) and the wage

[7] Ibid
[8] Ibid
[9] Ibid

rate.[10]" Neoclassical thinking explained production factors like profit for the capitalists, and wages for the workers were based on marginal inputs. Therefore, input of more capital and labor would provide for profit and more money for wages. The value of capital can change, it is not homogenous like labor or land and Cambridge, United States looked to fix that flaw in the teachings of Cambridge, England.[11] This brought more attention to the possibility of workers exploitation. It then became unclear if investment is what truly made profit or if it was the labor of workers that do not see that reflection in wages.

2.2.2 Cobb-Douglas Production Function

In the United States we see a strong influence of the Cobb-Douglas production function in modern days at the university level. This all began in the 1920s when the economist Paul Douglas was interested in aggregate level input and output.[12] This was after 1909-1918, a decade where the National Bureau of Economic Research (NBER) determined labor output to be 74% to wage paid. He partnered with Mathematician Charles Cobb to create a production function to make sense of the NBER's release.

$$Y = A\,K^{1/4}L^{3/4}.$$

Above was the original equation. This was derived from first assuming that the formula Y = F(K, L) governs relationship between output Y , capital K, and labor L.[13] F is assumed to be continuously differentiable. They then defined the variables

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[10] Controversy.", "Cambridge Capital. "Cambridge Capital Controversy." *International Encyclopedia of the Social Sciences*, Encyclopedia.com, 2019, www.encyclopedia.com/social-sciences/applied-and-social-sciences-magazines/cambridge-capital-controversy.

[11] Ibid

[12] Border, KC. *On the Cobb–Douglas Production Function*.

[13] Ibid

p = output price level, w = wage rate, r = capital rent rate

They then let K∗ (r, w, p) and L ∗ (r, w, p) maximize profit,[14]

$$pF(K, L) - rK - wL$$

The interior maximum first order are

$$pF_K(K^*, L^*) = r \tag{1}$$

$$pF_L(K^*, L^*) = w \tag{2}$$

(1) represents the partial derivative with respect to K while (2) is with respect to L. They then used their understanding from the NBER's 74% of output paid to labor to be a constant α.[15] This leaves us with

$$(1-\alpha)pF(K^*, L^*) = rK^* \tag{3}$$

$$\alpha pF(K^*, L^*) = wL^* \tag{4}$$

We divide (1) by (3) and divide (2) by (4) and take the integral of both. This leaves us with the results below.

$$\ln F(K, L) = \alpha \ln L + h(K) + c',$$

$$\ln F(K, L) = (1-\alpha) \ln K + g(L) + c,$$

When we combine the two we get the results below.

$$\ln F(K, L) = (1-\alpha) \ln K + \alpha \ln L + C$$

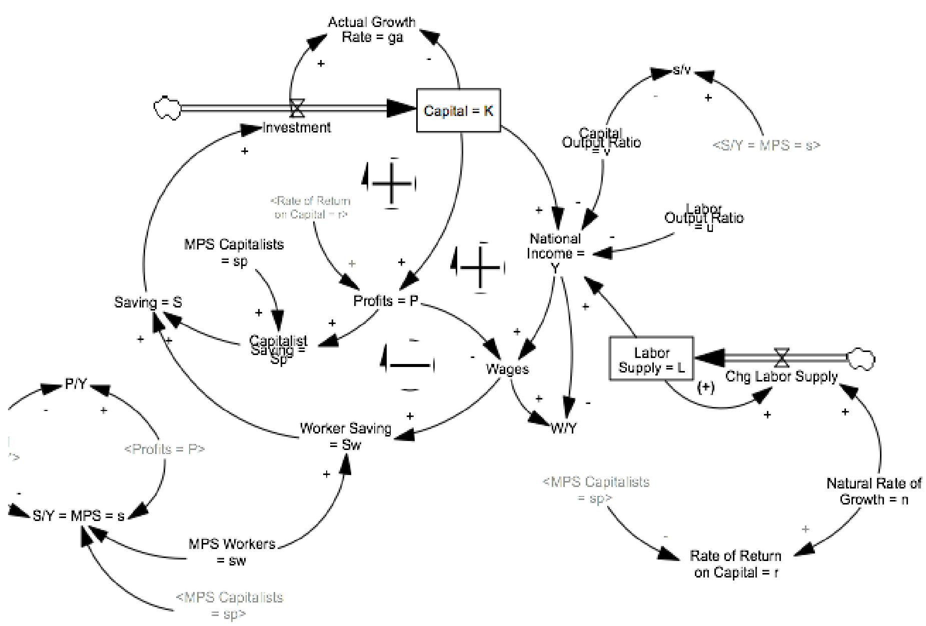
[14] Ibid
[15] Ibid

This leaves us with the Cobb Douglas Function.[16]

$$F(K, L) = AK^{1-\alpha}L^{\alpha}.$$

2.2.3 A Dynamic Model

The marginal products of the equation indicate that the more work a laborer puts in, the more that worker will see in wages. It also shows that capitalists benefit from the capital that they put in. Through this function, it is easy to suggest Capitalism as a just and fair system. However, Cambridge University in England challenged the Cobb-Douglas equation. Their critique pointed out that the Function is not dynamic. Luigi Pasinetti and Nicholas Kaldor are the authors of the dynamic approach. And, as shown below in a System Dynamics major feedback loop, the Vensim software allows you to alter inputs to get a dynamic look of output and better visualize what happens, based on feedback loops.



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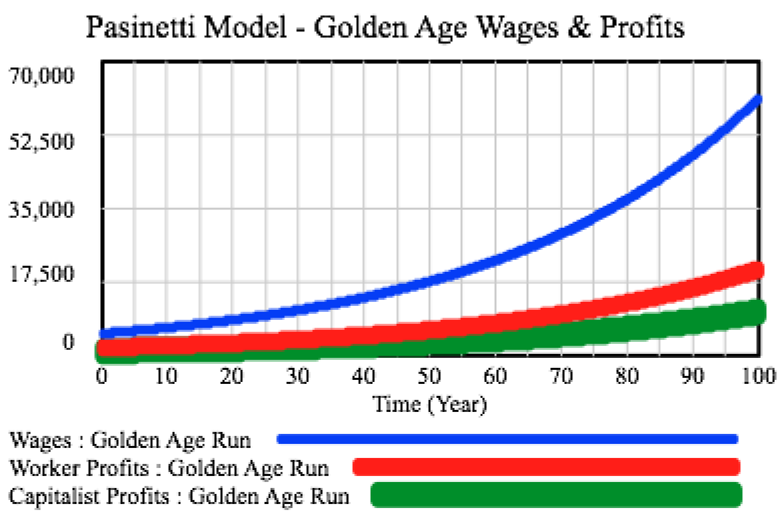
16 Ibid

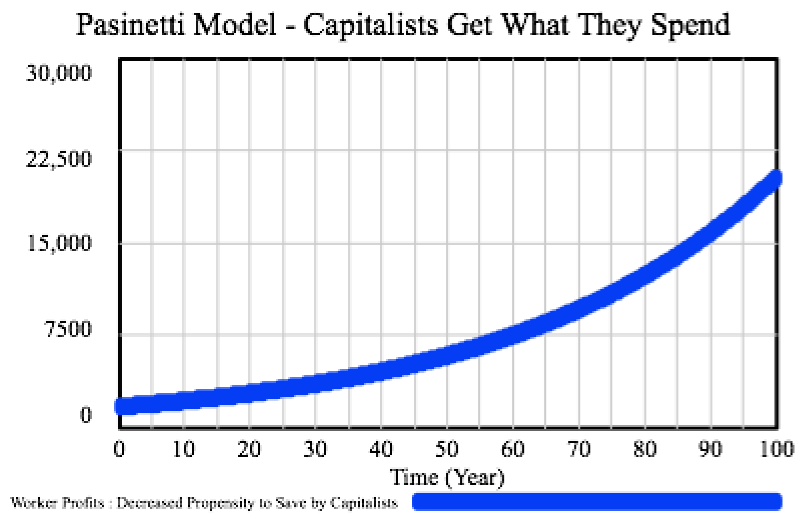
17 Radzicki, Michael. *Cambridge Controversies*.

Kaldor believed profit would be independent to that of workers savings in the long run. The model shows the same ideology in that it divides society is into capitalists and workers. When income per individual and population grow, we see savings grow for workers. He links profits with capitalists and wages with workers. He also assumes that all profits are saved unless they are spent to earn more (invested), and all wages are consumed. Pasinetti then used the same framework with a few modifications to strengthen the model. He added and acknowledged a golden age, and showed that workers spend what they earn and that capitalists earn what they spend.[18]

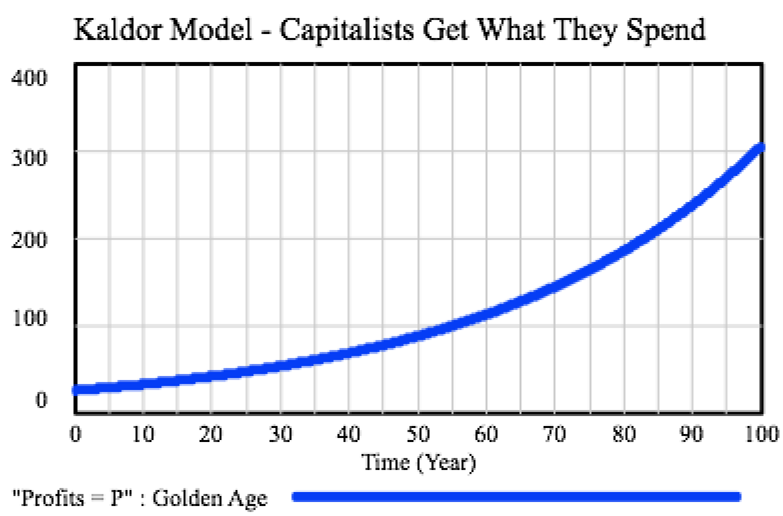


The Golden Age implies greater profits for all. We see wages increase, and profits for both workers and capitalists. It makes sense that workers profits increased faster than capitalists profits. In this era, there was more output, meaning more production and more workers. This allowed capitalists to profit more, but this enabled them to have more mouths to feed. Higher wages often mean people want to have more kids. A greater population to employ is more expensive for the capitalists.

[18] Ibid



As mentioned before, the more capitalists spend, the more they can gain in profit. However, workers cannot spend more to earn more, rather they have to spend what they earn to live. This era showed capitalists spending more. Decreasing propensity makes cheap currency and business more attractive for capitalists, which seems to benefit the workers with greater profits shown.



Kaldor model follows the same rules as the model above in an increase of National Income, workers and capitalists profits, and wages. These models help strengthen one another.

2.2.4 Modern Day American Politics

As shown before, more spending by businesses owned by capitalists means a better future for everyone. Under this model, it makes sense for President Trump to lower corporate tax. The United States now allows capitalists to spend more here and this serves as fuel to the economy. However, these models show that the worker-capitalist relationship goes beyond the amount of money put in and how hard a person works. These models can dynamically show that the capitalists have ultimate power in this society since they can create or take away opportunities from the masses who are in majority workers. Kaldor and Pasinetti are of the same school of thought as Kalecki, and through their models and results on power within capitalism we see the Marxist roots in their work as well as the import of profits to an economy.

This same ideology of profits takes us from the 20th Century to modern day American politics. Our Democratic Party seems to closely mimic some ideologies of Marxism. They believe workers are exploited and that free trade brings out the greed out of our economic system, where as the Republicans believe there is a competitive market of winners and losers that is apparent everywhere in the universe. In the current economic state of the United States, the stock market and employment rate show that higher profits make America a better place to live for the workers, however the Democratic party believes more should be done to bridge the gap between the wealthy and the poor. Understanding how profits would look in the future could tell us if workers will be exploited or if the winners will continue to win beyond any political perspective.

2.3 Data Science and Artificial Intelligence

The approach used by this research to make predictions regarding aggregate profits is data science. Data Science and Artificial Intelligence are innovative and proven to be the key motor that drives the direction of financial institutions' strategies today. Data Science is using science and mathematics formulas to make sense of data. In this project however we want to make predictions of Aggregate Profits of the US economy on a quarterly basis. We use artificial intelligence to make this possible. Artificial intelligence is the way computers, machines, robots, etc, use their intelligence to get an answer and make sense of this with "intelligence" as a human does. We used the RapidMiner software to predict profit in two different ways. We used Machine Learning and Deep Learning to make quarterly predictions.

Machine Learning is a subset of Artificial Intelligence, where as Deep Learning is a subset of Machine Learning. "Machine Learning is a form of artificial intelligence that can find answer of make predictions based on outside influence."[19] Outside influence meaning a programmer must give it a certain direction and must tell it what to look for. Deep Learning is a subset of Machine Learning and, on the other hand, does not need outside direction.[20] The algorithms must be given what to look for, and must also explain how to look for it. In the case of this project, we asked to forecast profit while telling the algorithm to find a pattern using four quarters of data points at a time.

Deep Learning uses neural nets to make forecasts based off information of the data. Each circle or neuron is given a numerical value from 0 to 1 to give it a weight to show how it impacts

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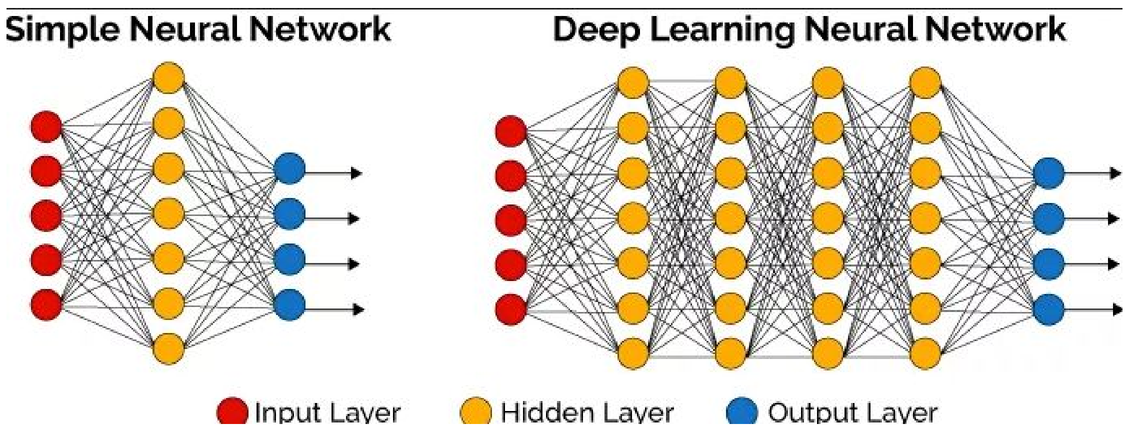
[19] Granville, Vincent. "Difference between Machine Learning, Data Science, AI, Deep Learning, and Statistics." *Data Science Central*, www.datasciencecentral.com/profiles/blogs/difference-between-machine-learning-data-science-ai-deep-learning.

[20] Ibid

the model. Several of these neurons are then compared to one another with the models input layer to its hidden layer, which effects the output layer (see image below).



[21]

Machine Learning is more common in different industries since it is simpler to explain while Deep Learning may get you a better answer with an explanation that is harder to follow and can be more difficult to trust.

[21] "Deep Learning Explained in 7 Steps." *Data Driven Investor*, 14 Feb. 2019, www.datadriveninvestor.com/2019/01/23/deep-learning-explained-in-7-steps/.

Chapter 3: Methodology

3.1 Benchmark

The purpose of this research is to predict aggregate profits for the US economy on a quarterly basis and four quarters ahead. To acquire data regarding the variables of the Levy-Kalecki equation, the source was the Federal Reserve Bank of St. Louis (FED). The file presents information on Investment, Dividend, Household Saving, Net Government Saving, ROW Saving and the Statistical Discrepancy from year 1947 to 2018 in a quarterly manner. As we took a deep dive into different forecasting methods, we came across a perspective that studied yield and maturity. Making predictions for a year, or four quarters ahead, allows researchers to examine economical factors such as possible recessions.

Though our project is focused on profits, the study by Estella and Mishkin provide a framework showing how predictions can affect how the economy will go, which will also affect firms, workers, and society as a whole. Their research showed that "the smaller the interest rate spread between long and short-term interest rates, the greater the probability of a recession four quarters ahead.[22]" This project uses the predictions of aggregate profits to dig deeper in the Levy-Kalecki studies of the past. Both Levy and Kalecki had communist economic thinking. Predictions from this project will provide insight on how workers are being treated in the US. From Communist theory we know there is a belief that the more profits a capitalist makes, the

[22] Stojanovic, Dusan, and Mark D. Vaughan. "The Yield Curve as a Forecasting Tool | St. Louis Fed." *The Yield Curve as a Forecasting Tool | St. Louis Fed*, Federal Reserve Bank of St. Louis, 25 June 2018, www.stlouisfed.org/publications/regional-economist/october-1997/yielding-clues-about-recessions-the-yield-curve-as-a-forecasting-tool.

more the workers are mistreated. This is the case specially if the workers do not see extra benefit from the increased profits.

Our approach for predicting profits was based off of the Levy-Kalecki Corporate Profit Equation. The table below is from an article that went out to test the equation and provided where to find certain information on the U.S. Bureau of Economic Analysis website.

Term	Reference
(+) Investment	NIPA Table 5.1 (Line 21 - Line 13)
(+) Dividends	NIPA Table 1.12 (Line 16)
(-) Household Saving	NIPA Table 5.1 (Line 8)
(-) Government Saving	NIPA Table 5.1 (Line 10)
(-) ROW Saving	NIPA Table 4.1 (Negative Line 29)
(-) Statistical Discrepancy	NIPA Table 5.1 (Line 42)
(=) Corporate Profits	NIPA Table 1.12 (Line 15)

When navigating the BEA website one may notice that the data only went up to 2013. However, the St. Louis Federal Reserve Economic Data (FRED) System provided information for the same variables on a quarterly basis. Data for each of the six variables had been updated to the most recent quarter, and such data is the one used for the predictions of our model. Each of the data points had the BEA as their source, though it was found on the St. Louis FRED website.

The software used for this research is RapidMiner. This software is filled with operators. These operators come with pre-coded functions that make the software extremely user friendly for individuals without a computer science background. Our first step was to get the St. Louis Fed data into RapidMiner. We decided to feed RapidMiner one Excel Spreadsheet with each of the variables titling each column and the data falling below the title chronologically.

We then Normalized the data. Normalizing data eliminates the units of measure and unifies the data. This makes it easier to compare how the data truly affects Aggregate Profits and the effect they have on each other. The previous study, basis for our own, divided by Gross

National Product (GNP) to normalize the data. After normalizing the data our last step was to generate profits for each quarter with the Generate Attribute Operator.

3.1.1 Assumptions

We assume that the next four quarters will be a time of steady profit growth. The most recent political reforms, specially the ones regarding corporate taxes, promote economic growth. It is important to note that growth that is too extreme can lead to a harsh downfall. Assuming companies understand this as well, we assume that slow and steady profit growth will be the way in which American economy behaves in 2019, in order to prevent a harsh period of decline.

But there is more to profits than just that. Profits are roughly the same as earnings, and earnings usually dictate how equity and bond markets will operate. Profits also explain the relationship between capitalist and workers, and our assumption here is that workers are not going to be treated fairly. Workers should be compensated for growth, Levy-Kalecki believed. We assume that the workers will not get rewarded as they should if profits do grow steadily as we believe they will. This assumption is based on the fact that they haven't been rewarded before.

3.2 Forecast

The normalized data to forecast in two ways. We used the windowing operator in which we predicted four quarters ahead for every quarter in the past as well as quarterly profits for 2019. A second method we had was using the Auto Model. This method gave predictions only one quarter ahead. This forecast model was a regression model. Though we have forecasts from it, our primary use of Auto Model was to show how each attribute impacted profit and if the impact was positive or negative.

After normalizing, we proceed into forecasting with Windowing. The outside influencer provided a window size of four, step size of one, horizon attribute selected was profit, and lastly a horizon size of four.[23] From there we received a profit forecast four quarters ahead for every quarter we had in our data set. The Windowing Operator is simple but a little more complex than the other operators we have used prior. The window size is what is being captured for the machine learning system to predict what is next.[24] Since we are predicting four ahead, we decided to capture four data points at a time. The step size is how many data points the window should move down after a forecast. We decided to do a step size of one, meaning it the window is moving down one quarter at a time. Using each quarter at a time will make predictions more accurate. The horizon attribute is what the operator focuses on in the window size, which in this case is profits. Lastly, the horizon size is how many quarters ahead one wants to predict, and we decided to forecast four quarters ahead as we determined in the Benchmark section of this chapter. The machine uses the data in the window size to find patterns and makes predictions and then moves forward with the step size to continue this process.

The Auto-Model forecast is self explanatory. The steps are to first load data, then select the task, prepare target and select inputs, then model types, and finally look at and analyze the results. The data loaded was the excel sheet that included the profit attribute. This method provides an array of results such as performance review, predictions, decision tree etc. All of which are further explained in the following chapter.

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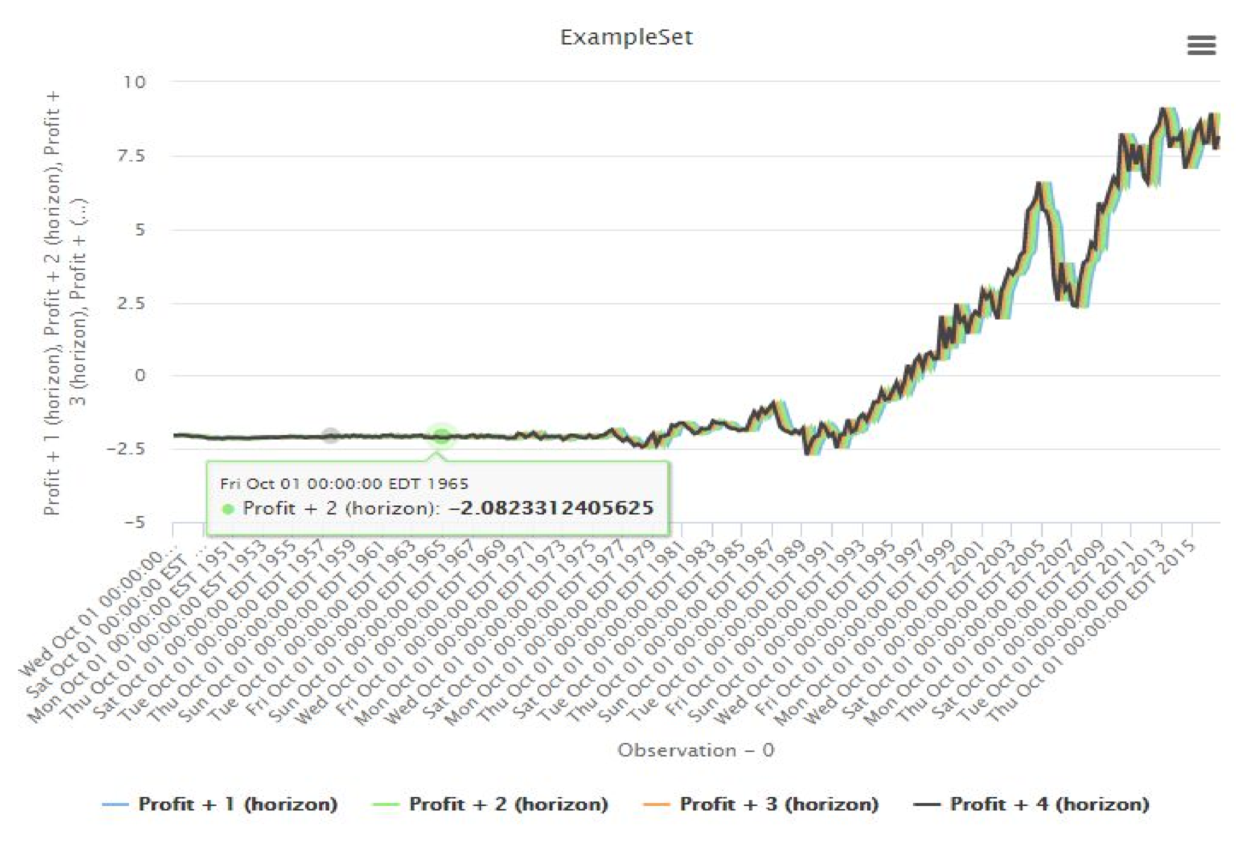
[23] Hofmann, Markus. "How to Use the Windowing Operator in RapidMiner - Data Mining." *YouTube*, YouTube, 23 Apr. 2018, www.youtube.com/watch?v=VKV3FrUliGw.

[24] GmbH, RapidMiner. "Windowing (Time Series)." *Windowing - RapidMiner Documentation*, docs.rapidminer.com/latest/studio/operators/modeling/time_series/windowing/windowing.html.

Chapter 4: Results & Analysis

4.1 Predictions and Validation

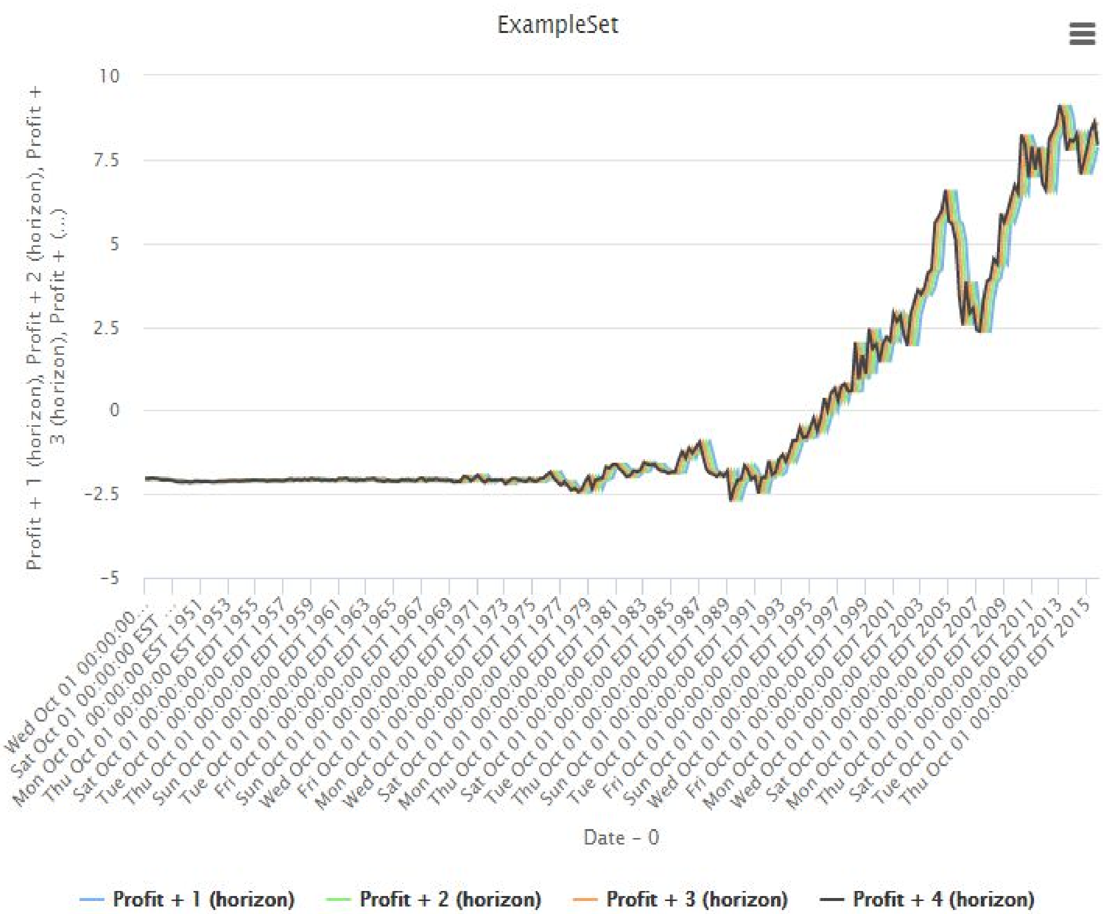
By using Machine Learning and Deep Learning operators provided by the RapidMiner Software this research found some impressive results. The windowing operator demonstrated the capabilities of Machine Learning. As we explained earlier, our goal was to predict Aggregate Profits a year in advance on a quarterly basis. The chart below shows how predictions moved over time.



One may zoom in and see the chronological results 7.859, 8.342, 8.603, and lastly 7.921. This predicts Aggregate Profit of the US economy to be 32.73 Billion for this upcoming year.

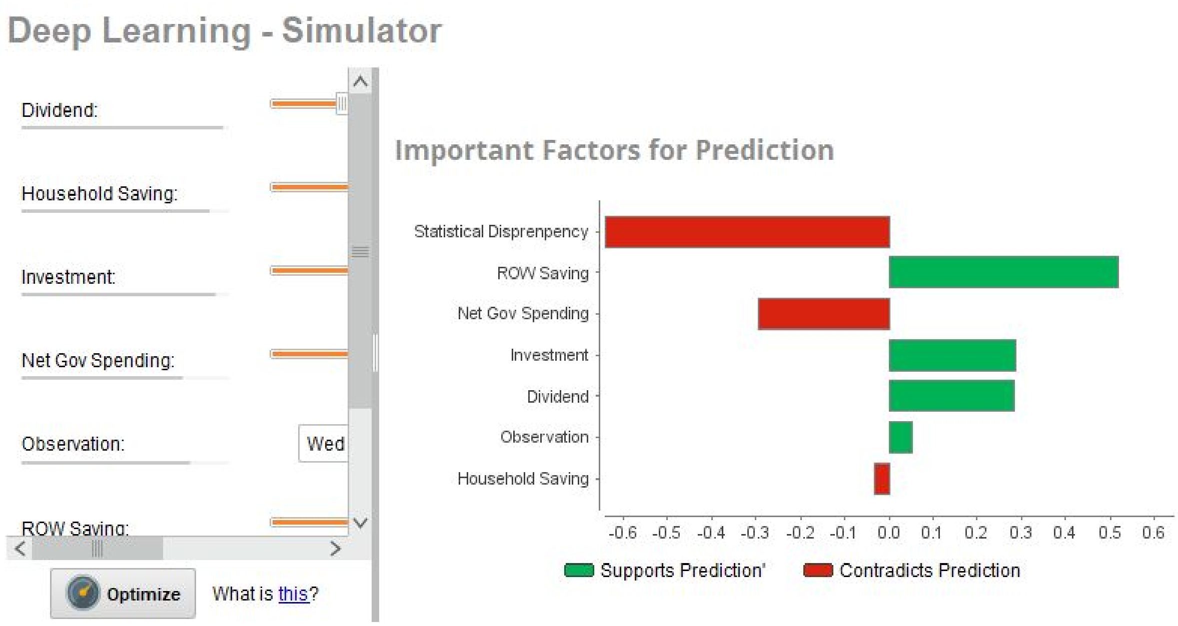
We are coming off of a 32.74 2018 performance. Though the model predicts a decline, it is very slight meaning this fiscal year should be economically rewarding to companies nationwide. The third quarter is predicted to be the most profitable quarter of 2019.

To revise the validity of our predictions, we chose to test the model against answers that we already had. By this we mean that we deleted the data from the last four quarter(2018 year), leaving the model with the 2017 fourth quarter being the last of the data given to the model. Below is the graph of profits without the 2018 quarters input data.



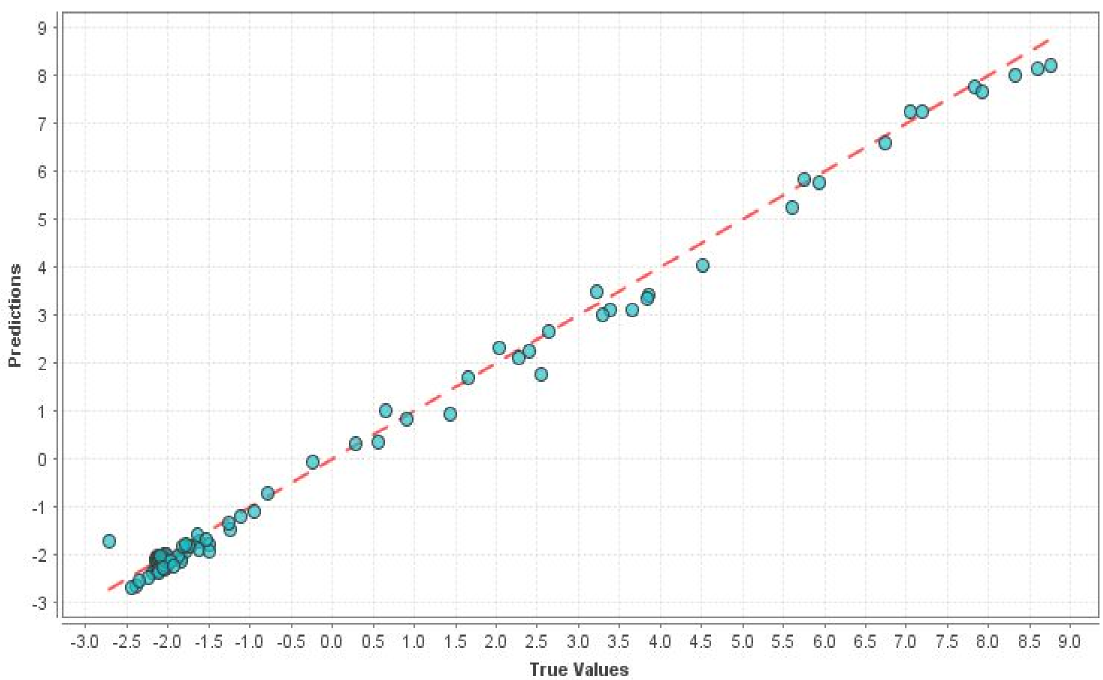
The model predicted the chronological 2018 quarters to be 7.422, 7.048, 8.251, and 8.031 while the actual quarterly profits were 7.944, 8.949, 7.691, and 8.155. The 4th quarter of 2018 was the closest prediction to the actual value. Though the predictions are not exact, we see 2018 Aggregate profits of 2018 to be roughly 33 billions while the model predicted 31 billion in profit this past year. Therefore, on an annual level this form of Machine Learning proves to be useful to getting close results.

We then used RapidMiner's Auto Model as another method of forecasting. We realized there were six different analyses that came with Auto Model. Each had a simulator that ranked the performance of each model based on the usefulness of the predictions, which are based on the attributes given from the data. The more useful the attributes, the higher the score is and the better the performance is as well. Deep Learning ranked the highest at 0.591, as shown in the image below.



The model does not predict four quarters in advance but only one quarter ahead at a time. We received a prediction of 8.030 for the first quarter of 2019. If that quarter represents a similar for the quarters to come, we can assume the Windowing Operators 32.73 annual profit predictions to also be supported by what we found in our Deep Learning Results.

We then followed the same strategy we did for our Machine Learning. We have the actual results of 2018 so we wanted to see how Auto Turbo would predict 2018's first quarter. 2018's actual first quarter was 7.944 and Auto Turbo predicted it to be 7.904. Deep Learning shows to be more accurate than Machine Learning. If this quarter represented the rest of the 2018 year that would be an approximate 32 Billion, which is close to the actual 32.74 Billion of this past. Rapid Miner's Deep Learning and Machine Learning tools seem to be truly effective.



Above is the Deep Learning Prediction Chart that gives an idea of how accurate or the model has been. Though comparing the actual values to predicted values proves to be a good way to validate results, RapidMiner has more ways to valid results. The Simulator, Correlation, and Root Mean Squared Error help validate the results and performance of the model. In order to understand the results one must first understand what they represent. All these methods are evaluators of regression analysis often used in the practice of Econometrics.

"RMS error measures the differences between values predicted by a model or an estimator and the values actually observed.[25]" These individual differences between the two values are called residuals, however when they are computed out-of-sample they are called prediction error. "68% of points on a scatter diagram are within one RMS error of the regression line, and about 95% are within two.[26]" The results are shown below.

We were given a 0.388 RMS error size, proving RapidMiner Deep Learning AutoModel tool to be very useful.

Correlation is a statistical technique that displays the relationship between the attributes and profits predicted in the model.[27] The correlation based on deep learning predictions and the attributes is incredibly high at 0.992, with 1 being the highest, 0 being no relation at all, and -1

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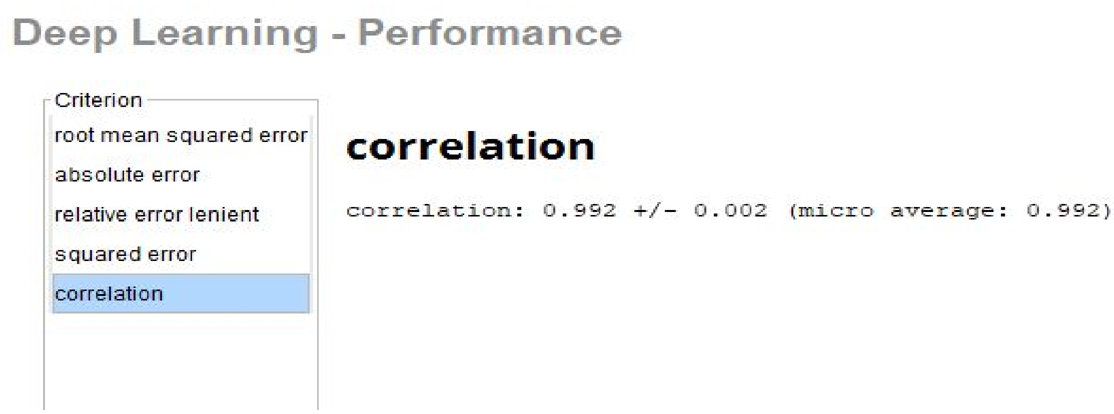
[25] Boundless. "Boundless Statistics." *Lumen*, courses.lumenlearning.com/boundless-statistics/chapter/r-m-s-error-for-regression/.

[26] Ibid

[27] "Correlation." *Correlation - Statistical Techniques, Rating Scales, Correlation Coefficients, and More - Creative Research Systems*, www.surveysystem.com/correlation.htm.

being negative correlation.



The Simulator is a useful tool because it shows which attributes contradict and support the model's results. It shows that Statistical Discrepancy, Net Government Saving, and Household Saving all are contradictory variables, while Observation, Investment, Dividend, and ROW Saving are all supporting variables.

4.2 Implications

These forecasts can be interpreted several different ways. Some include insights on the value of having two different methods of forecasting, which method is stronger, and how this affects the relationship between workers and capitalists in America from different perspectives. We used pure data science and artificial intelligence to make forecasts, without the use of economic theory. We now make sense of results and tie it into economic disputes of the past and how it even spreads in to politics today as we see with the views of Democrats vs Republicans.

The simulator used in Auto Model is very unique. It helped rank Deep Learning over the other 5 methods. But it also displayed contradicting and supporting attributes. What is most interesting here is that when the model is rerun without the contradictions, it gives a worse prediction, lower correlation, and lower simulator ranking score. This implies that contradictory attributes make for a better model.

The results received from Deep Learning and Machine Learning were also very interesting. Deep Learning gave us better results for quarterly predictions, however Machine Learning was helpful in that we knew how it was getting the predictions. We believe it is useful to have both since there are pros in cons with each of it. Deep Learning is said to get better with data while Machine Learning plateaus, so long term it is better to stick with Deep Learning for more accuracy. The RMS error result proves how close the predictions are from actual value and further support Deep Learning as an effective tool.

Overall the forecast point towards 30+ Billion in profits for the United States economy. This will bring companies much success at the expense of the working class as per Levy and Kalecki and the communist way of thinking. This thinking is more related to the Democratic Party in the country. On the contrary, the Republican side of the nation sees America becoming "Great Again". The forecast of 30+ billion in profit suggest a healthy job market, where people are making money and can make even more money by differentiating themselves in the marketplace.

4.3 Limitations

We had great success with our models. However, there is always room for improvement. To further improve our findings we believe the main focus could be on the windowing operator. We used a window size of four and a step size of one to predict and forecast the four quarters ahead of time. Using the actual values of 2018's four quarters we feel our window and step size could be tweaked to find even closer quarterly profit predictions. If this is done this could even make a case that the Windowing Operator would be better to use for understanding accurate predictions than the Auto Model, since the windowing operator takes outside tampering whereas Deep Learning does not. Our project is also only based on the Profit Equation of Levy-Kalecki. Too dive deeper maybe one could find an alternative profit equation and model that equation to test against Levy and Kalecki.

Chapter 5: Conclusion

The research we have done does not suffice for a comprehensive framework, as it does not account for a multitude of risks that are typically considered, and makes several simplifying assumptions. But from our research we do get impressive forecasts that can easily be replicated.

Our results suggest 2019 will be another profitable year from firms in the United States. Through these predictions we took a look at how this will affect the workers and capitalist relationship in this country, and used the tools of data science and artificial intelligence to help out with the analysis. One particular area this model could improve is in finding a better window and step size for the Windowing Operator to give even more precise forecasts. In addition to this, further research can be carried to compare the results using different profit equation ut the same forecasting methods as we used.

This model provides a foundation for research on the aggregate profits and its effect on America and so much more can be done with this research. There is a proven correlation between economic collapses, debt, and employment in the United States. We would like to challenge other undergraduates to maybe take the framework that we set forth and dive deeper to make predictions of the effects that aggregate profits could have on these specific factors of the economy. We also recommend RapidMiner as an incredible software with abundant tools for quick and precise results for future Economic Science Undergraduates here at WPI.

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